



Development Studies Research

An Open Access Journal

ISSN: (Print) 2166-5095 (Online) Journal homepage: <http://www.tandfonline.com/loi/rdsr20>

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To cite this article: Yacob A. Zereyesus, Aleksan Shanoyan, Kara L. Ross & Vincent Amanor-Boadu (2016) The determinants of household-level well-being in Northern Ghana, Development Studies Research, 3:1, 1-10, DOI: [10.1080/21665095.2016.1229128](https://doi.org/10.1080/21665095.2016.1229128)

To link to this article: <http://dx.doi.org/10.1080/21665095.2016.1229128>



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Published online: 20 Sep 2016.



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The determinants of household-level well-being in Northern Ghana

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ABSTRACT

Empirical analysis of the physical well-being at the household level was conducted for a sample of households in Northern Ghana using a Multiple Indicators Multiple Causes model. Physical well-being was indicated by the number of stunted children, number of wasted children, and number of underweight women. Results suggest that well-being at the household level is indeed represented by the latent variable and can be conceptualized in much the same way as the well-being of the individuals who constitute the household. Results show that the literacy of father and the number of dependents are associated with the largest shift in the underlying household's physical well-being. Locale and the household assets were also significantly associated with the collective underlying latent variable. The variability in household physical well-being is explained more by the number of stunted children in the household than any of the other indicators of household well-being.

ARTICLE HISTORY

Received 27 January 2016
Accepted 23 August 2016

KEYWORDS

Well-being; household analysis; MIMIC model; stunting; wasting; underweight

Introduction

Per capita income and expenditure have been widely used as measures of standard of living in the development literature. These indicators, while adequate for assessing economic well-being, may not always be sufficient for capturing overall well-being at the individual, household, or national level (Phipps 2002). In recent literature, the concept of development has been redefined from merely an economic concept to a more multidimensional concept encompassing social, economic, cultural, and political dimensions. Sen (1985, 1999) emphasizes that economic growth, although necessary, is not sufficient in itself to the achievement of a broader sense of development. Sen (1985, 1999) indicates that the fundamental purpose of development is to enlarge people's choices so that they can lead the life they want to.

Studies that model well-being as a multidimensional construct are in part the result of calls for broader approaches of measuring well-being and the inherent lack of satisfaction from using income alone as a measure of development (Alkire and Sarwar 2009). The multidimensional Human Development Index has been developed as an attempt to measure development and well-being by putting together indicators of life expectancy, educational attainment, and income into a composite index. The use of non-income indicators as measures of development is, then, an indication of the

growing acceptance of the multidimensional concept of development (Phipps 2002; Di Tommaso 2007; Krishnakumar 2007; Krishnakumar and Ballon 2008; Mabsout 2011).

A particular strand of research based on Sen's work on development and well-being is the application of the capabilities approach. The capabilities approach is centered on the notion that assessments of the well-being of a person should not primarily focus on resources, but on how well a person is able to function with the goods and services at his/her disposal (1985, 1999). One of the advantages of the capability approach is that it bypasses some of the difficulties encountered with financial resource-based approaches to welfare measurement, including (i) the inherent heterogeneity of people (in their ability to translate consumption into welfare) and (ii) the impact of public goods on welfare, for example, public health, education, and infrastructure, which is inadequately captured by per capita income alone (Sen 1999).

Many of the previous studies that modeled well-being by operationalizing the capabilities approach particularly focused on individual household members such as children (Phipps 2002; Di Tommaso 2007) or women (Mabsout 2011) or on the macro-level (Krishnakumar 2007). Based on previous works (Phipps 2002), Di Tommaso (2007) conceptualized the well-being of children using the capabilities approach providing a list of capabilities for Indian children. These capabilities encompass various dimensions of well-being such as *Life, Bodily*

Health, Bodily Integrity, Senses Imagination and Thought, Leisure Activities and Play, Emotions, and Social Interaction. Phipps (2002) compared the well-being of children in Canada, the USA, and Norway by looking at multiple dimensions of children's well-being. Martinez (2014) examined the physical health, cognitive ability, motor co-ordination, and emotional competence of preschool age children in poor rural communities in Mexico to model the multiple dimensions of children's well-being. It has also been shown that individual well-being is influenced by a complex set of interactions among family members (Alderman et al. 1996), which warrants a closer examination of the factors affecting the overall well-being of the household.

The collective well-being of household members is expected to influence and be influenced by the well-being of individual members due to the complex intra-household interactions. For example, if the income received by the breadwinners in a household is shared among household members including dependent children, then the physical well-being of breadwinners may affect directly or indirectly the well-being of the rest of household members, especially the well-being of dependents such as children and elderly. Research shows that parents' health condition can directly affect their children's health condition and use of health services (Olson et al. 2003). Several studies have modeled well-being on a family level for estimating the cost-effectiveness (CEA) of health interventions (Bonomi et al. 2005). Bonomi et al. (2005) delineated conceptual issues involved in representing the effects of health interventions at the family level. While measuring family-level assessments of CEA can be challenging, Bonomi et al. (2005) pointed out that data collected from multiple family members could be aggregated and analyzed into a family-level indicator. To the best of the authors' knowledge, however, none of the previous studies on well-being have modeled the collective household-level physical well-being as an underlying construct resulting from the interaction of individual members in the household.

The objectives of this paper are to bridge the gap in the literature by presenting (a) an empirical strategy for modeling physical well-being at the household level and (b) illustrative results from the analysis of households in Northern Ghana. The paper specifically aims to examine the association between household-level socioeconomic and demographic factors and the measure of collective physical health of the household as a dimension of well-being. Household-level physical well-being is measured by three indicators: the number of stunted children; the number of wasted children; and the number of underweight women. Stunting in children indicates chronic malnutrition resulting from prolonged periods of inadequate nutrition or recurrent or current illness. Stunting affects

the children's cognitive development, which may limit their productive capacity. Wasting, on the other hand, is typically an indication of acute undernutrition resulting from insufficient food intake and/or a highly infectious disease. The effect of wasting on the immune system can be severe, leading to increased severity and duration of existing diseases as well as susceptibility to infectious diseases (United Nations, World Health Organization 2010). For women in rural communities whose daily economic activities involve agricultural and similar physically demanding work, being underweight impedes their ability to perform their activities.

Methods for the empirical assessment of individual physical well-being are well established in the medical literature (Kosinski and Keller 1996; Jenkinson et al. 1997; Lim, 1999). For example, Westbrook, Talley, and Westbrook (2002) used the SF-12 measure to examine the physical and mental well-being of individuals with dyspepsia. Many of these methods rely on collecting self-reported information about an individual's ability to undertake moderate physical activities and whether their physical health limits the type or the extent of performed activities, as well as, the extent of bodily pain experienced and its interference with the individual's ability to work. While these methods provide good insight on an individual's physical well-being, the self-reported nature of the data introduces a certain level of subjectivity. The current study uses an alternative approach which relies on individual anthropometric measurement data. The anthropometric measurement data of individual household members, specifically of children and of women of reproductive age, are considered to represent collective physical well-being at the household level. In addition to children's and women's anthropometric measurements the model used in this paper incorporates the underlying household factors such as parental education, Household Hunger Scale (HHS) scores, dwelling characteristics, household assets, and other factors. The use of the Multiple Indicators Multiple Causes (MIMIC) model offers significant advantages over traditional structural equation models because the three health status indicators are not mutually independent. The use of multiple indicators is also beneficial because it reduces the effect of measurement error of any individual variable on the accuracy of the overall health results (Williams 2005).

Methods

Data

The empirical analysis is based on data obtained from Northern Ghana. Ghana is a country in West Africa,

with an estimated population of about 27 million. As a country, Ghana has been performing very well against the Millennium Development Goals of the United Nations (United Nations 2000). However, its performance has been mixed across regions (Osei-Assibey and Grey 2013). For example, the three northernmost regions were all found to be lagging behind the national average on poverty reduction goals. As a result of this uneven progress, the majority of development agencies, including the US Agency for International Development (USAID), turned their focus on the northern part of the country.

The data used in this study are from the 2012 population-based survey commissioned by USAID and conducted in the area above 8°N of Ghana, including the areas falling into the administrative regions of Brong Ahafo, Northern, Upper East, and Upper West but excluding the areas falling in Volta Region. The primary objective of the survey was to provide estimates of baseline indicators for USAID's Feed the Future initiative for the region covered by the survey. Among the indicators are children's anthropometry and women's anthropometry, which estimate children's and women's health statuses. The total sample of the population-based survey consisted of 4410 households and nearly 25,000 individuals. Two screening criteria were used to develop a subsample of households for the purposes of this study. For a household to qualify for this study its members must include: (i) children under the age of five and (ii) women in the reproductive age range from 15 to 49. The final subsample of households meeting screening criteria consisted of 1795 households and was representative of the population of households in Northern Ghana with young children and women of reproductive age. The data also included information on demographic and socioeconomic characteristics as well as women's and children's anthropometry. Sampling probability weights were used to make estimated results representative of the population in the study area.

The current research was approved for compliance with federal, state, or local rules, regulations and guidelines by the appropriate Research Compliance Office, the Committee on Research Involving Human Subjects which serves as the Institutional Review Board. Informed consent was obtained from all individual participants included in the survey.

Conceptual framework

The main outcome of interest in this study is a latent household physical well-being variable represented by the following three indicators: (i) the number of stunted children; (ii) the number of wasted children;

and (iii) the number of underweight women in each household. Children's health characteristics are determined using common anthropometric measures including height-for-age, weight-for-age, and weight-for-height. Well-nourished children 10 years or younger, regardless of ethnic background, have similar height and weight distribution and growth rates throughout the world (Cogill 2003). This allows for the development of a reference population which may be used to facilitate anthropometric comparisons. The process involves standardized z-scores developed for each child using the reference measures. The z-score, Z_{ij} , of the j th child for the i th indicator is estimated as:

$$Z_{ij} = \frac{(V_{ij} - V_{Mi})}{\sigma_{Mi}}, \quad (1)$$

where V_{ij} is the observed value of the i th indicator for the j th child, and V_{Mi} , σ_{Mi} are the median and the standard deviation of the i th indicator in the reference population. The World Health Organization (WHO) released new growth standards for children under the age of 60 months in 2006 using data from Brazil, Ghana, India, Norway, Oman, and the USA (United Nations, World Health Organization 2006). Based on these new data, WHO recommended that when the standardized z-scores of the height-for-age, weight-for-age, and weight-for-height are less than 2 standard deviations below the median measurement for the reference group, then that child is stunted, underweight, and wasted, respectively. For the purposes of this study, the numbers of stunted and wasted children were counted separately on a per household basis.

The measurements on stunting and wasting provide the nutritional status of a given child from two different perspectives. For example, stunting indicates chronic malnutrition resulting from prolonged periods of inadequate nutrition or illness. It may, thus, be interpreted as an indication of poor conditions in the child's environment. Wasting, on the other hand, is typically an indication of acute undernutrition resulting from insufficient food intake and/or a highly infectious disease (WHO 2010). The simultaneous use of these variables is based on the following important relationship between the two indicators. A given child exhibits the following three health conditions indicated by the z-scores of the height-for-age and weight-for-height scores: (i) a child is neither stunted nor wasted; (ii) a child is either stunted or wasted; or (iii) a child is both stunted and wasted. In the latter case, a stunted child who has been suffering from chronic malnutrition as a result of prolonged periods of inadequate nutrition may also become wasted if the child happens to be exposed to short-term malnutrition or to a highly

infectious disease incidence. Based on such implications, the underlying overall health status of a child is determined by the particular scores of these two indicators at any given time.

Women's physical health characteristics (underweight) are determined using Body Mass Index (BMI), which is a commonly used indicator for determining body composition and health-risk conditions (Wells and Fewtrell 2006). Women with BMI of less than 18.5 kg/m² are considered underweight. Women who are underweight spend more time performing their daily activities (Kennedy and Garcia 1994), and they are at a higher risk of developing functional disabilities (Ferraro et al. 2002). Research shows that having a healthy (or normal) BMI increases the capacity to perform domestic and agricultural activities (Kennedy and Garcia 1994).

The explanatory variables included in the model can be grouped in two broad categories: socioeconomic and demographic. Socioeconomic variables include household's access to credit, crop production (per unit yield), household's participation in off-farm employment, HHS, as well as variables indicating quality and standard of living conditions such as number of persons sleeping in a room, availability of safe drinking water, and ownership of a refrigerator. HHS indicator is a recently developed indicator which measures the quantity of food accessible to a household (Ballard et al. 2011). Household hunger is an extreme case of a household's food insecurity. Household hunger is an extreme case of households food insecurity. HHS is estimated from answers to questions about food accessibility and the frequency of food insecure situations over a four-week recall period. Household's access to credit is cited as an important factor in determining the livelihood of resource-poor households. Almost all the households in the study area are engaged in farming as their primary activity (Zereyesus et al. 2014).

The per unit crop production variable accounts for differences in productivity differentials between the individual households. The non-farm sector also plays an important role in providing an alternative source of income and employment for resource-poor households. The literature is replete with evidence that non-farm income could provide self-insurance against likely shocks, overcome farm credit constraints and enhance farm investment, absorb labor surplus, and ultimately improve the financial well-being of households through increased total income (Barrett, Reardon, and Webb 2001; Reardon, Berdegue, and Escobar 2001; Hoang, Pham, and Ulubasoglu 2014). The demographic variables include: the literacy status of the mother and of the father, the proportion of dependents in the household, and location (urban vs. rural).

Summary statistics, along with variable definitions, are presented in Table 1. Collinearity among the study's variables was examined by checking the tolerance and variance inflation factor (VIF) values. The VIF values for all the variables were below 4, which were within the acceptable range, suggesting that these variables were not collinear.

Analysis

The MIMIC model is used in the analysis. The MIMIC model is a special specification of the structural equation modeling (SEM) approach consisting of a structural and a measurement equation. This model is especially useful when multiple dependent variables need to be tied together into a 'single' variable (Di Tommaso 2007; Del'Anno 2007; Mabsout 2011; Ross et al. 2015). The previous uses of the MIMIC model included the study of children's well-being in India linking variables such as physical health, imagination and thought, and the

Table 1. Summary statistics of the principal variables (N = 1,795).

Variable	Description	Mean	Standard deviation
<i>Demographic and socioeconomic variables</i>			
Education of mother	1 = Some formal educational training; 0 = No education	0.06	0.24
Education of father	1 = Some formal educational training; 0 = No education	0.16	0.37
Dependents	Proportion of dependents in the household	0.52	0.14
Credit	1 = Household has access to credit; 0 = Otherwise	0.39	0.49
Per unit yield	Per unit yield of crops (kg/acre)	24.61	404.09
Off-farm income	1 = Household has off-farm income ; 0 = Otherwise	0.65	0.48
<i>Household and location variables</i>			
Locale	1 = Urban; 0 = Rural	0.21	0.41
HHS	1 = Moderate to severe hunger; 0 = Little to no hunger	0.36	0.48
Fridge	1 = Household own refrigerator; 0 = Otherwise	0.05	0.22
Persons per room	Number of persons per sleeping room	2.3	1.41
Safe drinking water	1 = Household drinking water safe; 0 = otherwise	0.69	0.46
<i>Household's health status variables</i>			
Number of stunted children	Number of stunted children per household	0.48	0.69
Number of wasted children	Number of wasted children per household	0.16	0.41
Number of underweight women	Number of underweight women per household	0.14	0.41

leisure and play activities of children (Di Tommaso 2007), women's health, by linking BMI, anemia status (Mabsout 2011), and their dietary diversity (Ross et al. 2015). The MIMIC model has also been used to link multiple indicators and multiple causes in other fields. For example, Dell'Anno (2007) applied the MIMIC model to study the factors influencing the underground economy or black market in Portugal. For the purposes of this study, the MIMIC model provides significant advantages over traditional structural equation models because it addresses the issues arising from the fact that the three physical well-being indicators used as the dependent variables are not mutually independent.

Following Joreskog and Goldberger (1975) and Spanos (1984), the latent household's physical well-being, Y^* , is determined by a set of observable exogenous causes $x_1 \dots x_n$

$$Y^* = \alpha_1 x_1 + \dots + \alpha_n x_n + \varepsilon. \quad (2)$$

Denoting $X = (x_1 \dots x_n)'$ and $\alpha = (\alpha_1 \dots \alpha_n)'$ we may express the relationship in vector form with Equation (3), with the error term, ε , assumed to have a zero mean and a unity standard deviation:

$$Y^* = \alpha'X + \varepsilon. \quad (3)$$

The latent household's well-being, Y^* , above is assumed to determine the observable endogenous well-being indicators of interest in this study, y_1, \dots, y_m , as follows:

$$y_1 = \beta_1 Y^* + v_1; \quad y_2 = \beta_2 Y^* + v_2, \dots; \quad y_m = \beta_m Y^* + v_m.$$

Denoting $Y = (y_1, y_2, \dots, y_m)'$, $\beta = (\beta_1, \beta_2, \dots, \beta_m)'$, and $v = (v_1, v_2, \dots, v_m)'$ we may express the above relationship in vector form with Equation (4), with the error terms in v being mutually independent error terms:

$$Y = \beta Y^* + v. \quad (4)$$

It is assumed that $E(\varepsilon v) = 0$, $E(\varepsilon^2) = \sigma^2$, and $E(vv') = \Theta^2$, with Θ being $m \times m$ diagonal matrix.

The MIMIC model, which is the reduced form of equations 3 and 4, presents the observable indicators, Y , as a function of the observable exogenous variables, X , suggesting that:

$$Y = \pi'X + v, \quad (5)$$

where $\pi = \alpha\beta$ and $(\beta\varepsilon + v) = v$.

The MIMIC model is identified when there are at least two observable indicators and at least one exogenous variable, provided that one of the factor loadings of the indicators is set equal to one in order to form the scale of the latent variable. The problem defined in this research meets this threshold requirement for

identification and, hence, qualifies for being solved with the MIMIC model.

In our model, the exogenous variables have different units, making a comparison of their estimated parameters uninformative. As noted by Bollen (1989), to enhance the information content of the estimated parameters for comparison purposes, the coefficients are standardized to eliminate their dimensions. This is the same approach used traditionally by economists when they employ elasticities to determine the relative importance of the contributions of variables in a model. Thus, this standardization facilitates the determination of which independent variable has the largest effect on the dependent variable. The problem with the elasticity is that the contribution approaches infinity as the point of the estimation (which is often the mean) approaches zero. When the mean equals zero, then there is no solution.

To avoid this risk, we use other dimensionless indicators to determine relative influence (Ross et al. 2015). The standardized regression coefficients, $\hat{\alpha}_{ij}^s$ and $\hat{\beta}_{ij}^s$, are defined as follows:

$$\hat{\alpha}_{ij}^s = \hat{\alpha}_{ij} \left(\frac{\hat{\sigma}_{jj}}{\hat{\sigma}_{ii}} \right) \text{ and } \hat{\beta}_{ij}^s = \hat{\beta}_{ij} \left(\frac{\hat{\sigma}_{jj}}{\hat{\sigma}_{ii}} \right),$$

where i is the dependent variable, j is the explanatory variable, $\hat{\sigma}_{ii}$ and $\hat{\sigma}_{jj}$ are the model-predicted standard deviations of the i th and j th variables, respectively. The standardized coefficients show that mean response in standard deviation units of the dependent variable for a one standard deviation change in the explanatory variables, *ceteris paribus*. The standardized regression coefficient using δ is thus a special case of elasticity evaluated at a point where the independent variables shift from 0 to $\hat{\sigma}_i$ and its effects on the dependent variable shift from 0 to $\hat{\sigma}_j$.

Results

The results of the analysis are presented in Tables 2 and 3. Because sampling probability weights were used during estimation of the models, goodness-of-fit statistic are given by the standardized root mean squared residuals (SRMR) scores. The SRMR scores for the overall models are less than 0.05, indicating a good fit of the models. The eigenvalue stability condition test for the two models also reveals that the respective eigenvalues lie inside the unit circle. Therefore, these SEM models satisfy the stability conditions. More goodness-of-fit test results and discussions are presented in the next subsection for these models without applying the sampling probability weights.

Table 2. Results of the measurement MIMIC model relating the collective household well-being and the indicators in Northern Ghana ($N = 1,795$).

Health indicators	Standardized coefficient	Standard error
Number of stunted children	0.342*	0.058
Number of wasting children	0.161*	0.026
Number of underweight women	0.186*	0.031

*significance of standardized coefficients at the 99% confidence level. The R^2 value is 0.395.

The result of the measurement model relating the latent variable with its indicators is shown in Table 2. The estimated coefficients on all of the indicators are statistically significant at the 1% level confirming that the constructed underlying single common latent variable is representative of the three indicators. A household will have a lower score in the latent well-being if it has a high number of either or all of the indicators. For example, the positive sign on the number of stunted children variable implies that households with a higher number of stunted children are associated with lower latent household's physical well-being scores. In other words, the lower the number of any or all of the indicators in the household, the better the overall household's well-being is. The results in Table 2 also reveal the magnitude and strength of the association between the household's latent well-being status and its indicators. The coefficients show that the variability in the underlying common latent variable is explained to a larger extent by the number of stunted children than by any of the other indicators. For example, the coefficients show that a one standard deviation shift of the latent variable is associated with a change of 0.33 standard deviation of the number of stunted children in the household, higher than the association with any of the other indicators.

Table 3(a) presents the results of the structural model in standardized coefficients. Variables indicating literacy of the father and proportion of dependents in the household are associated with the well-being variable at the 1% significance level. It is important to remind the reader that the negative sign on the coefficient must be interpreted as a positive effect on the household physical well-being status due to the fact that the household's well-being is inversely related to the indicators that define it (i.e. number of stunted and wasted children, and underweight women). Accordingly, the results indicate that the households where the father is literate are associated with better underlying latent well-being. This further supports previous findings in Ghana (Thomas 1994) where the education of parents had a positive and significant effect on their children's height. The number of persons per sleeping room is associated with the latent variable at the 5% significance level, and the urban locale and the participation of the

household in off-farm work are significantly associated with the latent variable at the 10% significance level.

Literacy of the mother, household's access to credit, HHS, per unit yield of crops, and the availability of a fridge and safe drinking water in the household are not statistically associated with the latent variable at the conventional significance levels. Although not statistically significant, the direction of the coefficients on both the availability of a fridge and safe drinking water in the household is consistent with the theory and expectations given that these two features capture the quality of a household's living standard. For example, research shows that amenities such as the availability of health services in general and clean drinking water and sanitation in particular matter in child health and nutrition (Charmarbagwala et al. 2004). Similarly, the sign on the literacy level of the mother may suggest positive association of mother's education with the latent household well-being, which aligns with the expected direction of possible relationship between literacy and health status.

Because the results are reported in standardized coefficients, relative comparisons can be made. The proportion of dependents in the household variable is associated with the largest shift in the standard deviation of the latent variable. The magnitude of the coefficient on the dependent variable shows that a one standard deviation change in this variable is associated with a 0.43 standard deviation change in the health status variable, holding all other variables constant.

An additional level of analysis is conducted to examine the robustness of the results. This is done by restricting the sample to only the Northern Region which accounts for 72% of the total population. The objective is to examine the general comparability of the results from a Northern-Region-only sample with the total sample including observations from Brong Ahafo, Northern, Upper East, and Upper West regions. The estimated results of the analysis of the subsample from the Northern Region are presented in Table 3(b). In general, controlling for the Northern-Region-fixed effect has not changed much of the results of the basic model in terms of the direction of relationship and the significance of the coefficients as reported in Table 3 (a). For example, holding all other variables constant, households in the Northern Region that have a higher

Table 3. Results of the structural MIMIC model for the collective household (a) well-being in Northern Ghana ($N = 1,795$) and (b) well-being in Northern Region of Ghana ($N = 1,295$).

Explanatory variables	Standardized coefficient	Standard error
(a)		
Education of mother	-0.047	0.058
Education of father	-0.186***	0.065
Dependents' ratio	0.434***	0.081
Credit	0.088	0.072
Per unit yield	0.016	0.047
Off-farm income	0.120*	0.072
Locale	-0.117*	0.066
HHS	0.025	0.074
Fridge	-0.068	0.062
Persons per room	0.197**	0.077
Safe drinking water	-0.008	0.075
(b)		
Education of mother	-0.066	0.064
Education of father	-0.173**	0.072
Dependents' ratio	0.410***	0.102
Credit	0.127	0.086
Per unit yield	0.054**	0.022
Off-farm income	0.067	0.086
Locale	-0.032	0.081
HHS	0.036	0.090
Fridge	-0.056	0.086
Persons per room	0.329***	0.110
Safe drinking water	-0.072	0.090

***, **, *significance of standardized coefficients at the 99%, 95% and 90% confidence level, respectively. The SRMR for the model specification is 0.018 and the R^2 is 0.11.

proportion of dependents are associated with a higher number of the indicators: stunted children, wasted children, and underweight women, implying a negative effect on the overall latent well-being variable. Similarly, it was observed that the literacy of the father was positively and significantly associated with greater well-being within the household.

Model diagnostic test results

Data used for the analysis are collected on the basis of a population-based survey design, and hence the use of sampling probability weights is necessary while estimating the models. It is indicated that the SRMR scores for the overall models were less than 0.05, indicating a good fit of the models. However, additional goodness-of-fit tests are conducted to validate the robustness of the results and the stability of the models, but this time without applying the sampling probability weights so that these additional model fit tests could be done. The tests conducted include the model chi-squared test indicated by the likelihood ratio (LR) value, root mean squared error of approximation (RMSEA) of the population error, and the Comparative Fit Index (CFI) with the baseline model. A value of RMSEA close to zero indicates the best fit. The CFI is an index that measures the relative improvement of the model over that of a baseline model, with a value closer to 1 indicating a better fit (Kline 2011).

These tests are applied to the full model comprised of the entire four regions, as well as for the Northern Region model only. Results of these tests are presented in Table 4.

For the model estimated using the entire data of the four regions, the LR test of the model vs. the saturated model resulted with a $\chi^2_{(25)}$ value of 71.02 ($p = .000$). The saturated model is the model that fits the covariances perfectly. Based on the results, at the 5% or less level of significance, the null hypothesis that the model fits as well as the saturated model is rejected. However, the chi-squared goodness-of-fit test can be overly influenced by sample size, correlations, variance unrelated to the model, and multivariate nonnormality (Kline 2011). Furthermore, under the population error, the RMSEA and its 90% confidence interval, and pclose fit (the p -value for a test of close fit, i.e. $\text{RMSEA} < 0.05$) are provided. Based on the results (RMSEA of 0.032 with 90% lower bound and upper bound values of 0.023 and 0.041, respectively), the fit is close because the lower bound of the 90% CI is below 0.05. Similarly, the null hypothesis that the fit is poor is rejected because the upper bound is less than 0.10. The pclose fit also provides the probability that the RMSEA value is less than 0.05, which is interpreted as the probability that the predicted moments are close to the moments in the population. Because the pclose is high (1.00), it can be concluded that the model fit is close. Furthermore, the CFI value for the model is 0.425 and the closer this value to 1, the better the fit it is.

Table 4. Values of fit statistics for the two models.

Fit statistic ^a	Description	Model	
		All regions	Northern Region
LR			
$\chi^2_{(25)}$	Model vs. saturated	71.024	30.671
$p > \chi^2$		0.000	0.200
Population error			
RMSEA	Root mean squared error of approximation	0.032	0.013
90% CI, lower bound		0.023	0.000
90% CI, upper bound		0.041	0.027
pClose fit H_0	Probability RMSEA ≤ 0.05	1.000	1.000
Baseline comparison			
CFI	Comparative Fit Index	0.425	0.882
TLI	Tucker–Lewis Index	0.172	0.829
Size of residuals			
SRMR	Standardized root mean squared residual	0.018	0.014
CD ^b	Coefficient of determination	0.285	0.324

^aThe goodness-of-fit test results are conducted without the application of survey sampling weights.

^bCD is like an R^2 for the whole model, and a perfect fit corresponds to a CD of 1.

For the model estimated using the Northern Region only, the LR test of the model vs. the saturated model resulted with a $\chi^2_{(25)}$ value of 30.671 ($p = .200$) implying that, at the 5% or less level of significance, the model fits as well as the covariances as well as the saturated model. Under the population error, the RMSEA of 0.013 with 90% lower bound and upper bound values of 0.000 and 0.027, respectively, indicates a close fit of the model. The pclose also provides the probability that the RMSEA value is less than 0.05, which is interpreted as the probability that the predicted moments are close to the moments in the population. Again for this model, the pclose is high (1.00) implying the model fit is also close. Finally, the CFI value for this model is 0.882 and the closer this value to 1, the better the fit it is. It is indicated in the discussion section of the results that both models provided similar results in terms of the direction of relationship and the significance of the coefficients of the variables. Based on the diagnostic test results, it appears that the model restricted to the Northern Region only as opposed to the full model of all the four regions seems to fit the data better in all the tests.

Conclusion and implications

This study aims to improve the understanding of how the complex intra-household relationships and socioeconomic factors impact the overall household's physical well-being. It presents an empirical strategy for modeling the interaction between household-level socioeconomic and demographic factors and the measure of collective well-being at the household level. The empirical analysis utilizes detailed data from Northern Ghana on demographic and socioeconomic characteristics of 1795 households, as well as specific anthropometric measures of women and young children in those households.

Methods incorporate the MIMIC model as a special specification of the SEM approach particularly well suited for the analysis involving multiple dependent variables which are not mutually independent.

The results illustrate several notable relationships between the household-level socioeconomic characteristics and the measure of household's latent physical well-being as defined by the number of stunted children; the number of wasted children; and the number of underweight women of reproductive age. First, the results indicate that the literacy of the father in the household positively influences the household's collective physical well-being. This result is consistent with the theory and previous empirical evidence on the positive return of education on the overall health and well-being of individuals. Second, the results indicate the positive effect of the quality of living conditions, and the urban locale on collective health and well-being of the household members. Third, the results show negative association between the household's overall well-being and the relative number of dependents and breadwinners among the household members.

It is important to note that while the household's physical well-being is a broader construct that extends beyond what can be captured through anthropometric measures of individual household members, the outcome variables used in the study (e.g. number of stunted and wasted children and number of underweight women in the household) can serve as good indicators of health. This paper presented an empirical strategy to model household's physical well-being as a function of individual member's physical well-being, which in turn is a function of long-term nutritional quality and disease exposure of the household. This line of modeling strategy has recently been adopted in development economics from psychometrics literature and uses the concept of latent variable

based on a set of observed indicators that are known to be noisy in nature (Di Tommaso 2007). The results shed light on the complex relationship between household-level socioeconomic factors and the collective physical well-being of its members. Although intuitive, these relationships have not been empirically examined at the household level in the literature, which underscores the contribution of this study to the development literature.

The contribution of this study is twofold. First, it presents an empirical strategy for modeling health and well-being at the household level. This helps extend the literature on well-being as a multidimensional and multilayer concept as demonstrated by a growing number of studies that have been applied to varied units of analysis (Phipps 2002; Di Tommaso 2007; Krishnakumar 2007; Krishnakumar and Ballon 2008; Mabsout 2011). Second, it provides illustrative empirical results from Northern Ghana – a region of special interest to the development community. Although the sample is representative of a specific population of inference in Northern Ghana, the robustness tests indicate that the results are generalizable to the broader population of the region. It is important to point out that information on the physical well-being of household members (e.g. anthropometric measurements of men and other health indicators of household members) could enhance the model significantly. Finally, although the results of this study shed light on the complex relationship between household-level socioeconomic factors and the collective physical well-being of its members in the context of Northern Ghana, further research and policy simulations are necessary to provide specific and relevant recommendations by considering composite household-level indicators such as health, social interactions, cognitive ability, motor co-ordination, and emotional competence that can significantly affect the quality of life.

Disclosure statement

No potential conflict of interest was reported by the authors.

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